E-ISSN: 2717-2937 | P-ISSN: 2783-1337

International Journal of Research in Industrial Engineering

IJRIE

www.riejournal.com

Int. J. Res. Ind. Eng. Vol. 12, No. 1 (2023) 21–42.

Paper Type: Research Paper

# A Mathematical Model for Robust Landing and Take-Off Scheduling at an Airport Considering Runway Disturbances

**Parviz Tohidi Nasab[1], Mohsen Vaez-Ghasemi[2,*], Ghasem Tohidi[3]**

[1] Department of Industrial Engineering, Central Tehran Branch, Islamic Azad University, Tehran, Iran; p.tohidi94@gmail.com.
[2] Department of Mathematics, Rasht Branch, Islamic Azad University, Gilan, Iran; mohsen.vaez@gmail.com.
[3] Department of Basic Sciences, Central Tehran Branch, Islamic Azad University, Tehran, Iran; ghatohidi@yahoo.com.

**Citation:**

Tohidi Nasab, P., Vaez-Ghasemi, M., & Tohidi, G. (2023). A mathematical model for robust landing and take-off scheduling at an airport considering runway disturbances. *International journal of research in industrial engineering, 12*(1), 21-42.

Received: 30/12/2021 Reviewed: 01/02/2022 Revised: 09/03/2022 Accepted: 14/05/2022

## Abstract

The Aircraft Scheduling Problem (ASP) refers to allocating each aircraft to the optimal take-off and landing time and the appropriate runway. This problem is the allocation of aircraft to the desired runway so that the total damage due to delays or haste in landing or take-off of all aircraft is minimized. Runway allocation, landing and take-off sequences, and scheduling for each aircraft must be done in a predetermined time window. Time should also be considered as the time of separation between landings and take-offs due to the wake vortex phenomenon. In general, the purpose of such problems is to make maximum use of the runway. Therefore, in this study, a mathematical model of robust landing and take-off scheduling at an airport is provided, assuming no access to the airport runway at certain times. Moreover, delays and haste in landing and take-off on the runway, limited access to aircraft, runway repair time, and the possibility of runway disturbances are investigated. Robust optimization is used to deal with uncertainty at take-off and landing times. Finally, Genetic and Imperialistic Competitive Algorithm (ICA) are used to evaluate and analyze the problem because it is NP-HARD problem. The results indicate the ability of the proposed algorithms to find high-quality solutions in a short computation time for problems up to 7 runways and 60 aircraft.

**Keywords:** Aircraft scheduling problem, Robust optimization, Genetic algorithm, Imperialistic competitive algorithm.

## 1 | Introduction



Nowadays the high volume of transportation is done by aircraft (plane), which is very expensive compared to other transportation systems. Some of these costs include damages due to delays and haste in landing and flight, which include significant figures, so saving them leads to a significant reduction in total costs. Therefore, special importance is given to the optimal landing and take-off scheduling. Rising fuel prices have made this even more important. This problem is the allocation of aircraft to the desired runway so that the total damage due to delays or haste in landing or take-off of all aircraft is minimized. In general, the purpose of such problems is to make maximum use of the runway.

Corresponding Author: mohsen.vaez@gmail.com

https://doi.org/10.22105/riej.2022.322212.1275

Air transportation plays a significant role in the movement of passengers and freight, and this role is becoming more important day by day so that air transportation accounts for a significant share of the transportation problem. There is a growing demand for air travel so it is not unexpected that the demand for air travel will multiply in the coming years. This has created many problems in recent years such as delays, traffic, and air accidents.



The scheduling problem is one of the most important problems in the world today that has a significant impact on increasing the efficiency of production and transportation systems Zeng et al. [1]. Scheduling refers to the allocation of limited resources to activities that require that resource and is a kind of decision-making activity that is done to optimize one or more goals Ng et al. [2]. As a result, aircraft scheduling is one of the most important problems and factors affecting the transportation, industry and customer satisfaction. This problem is to determine the optimal sequence of landing or take-off and assigning them to different and same runways, taking into account the limitations of parking spaces so that the total cost of flight delays is minimized Lambelho et al. [3]. In other words, the Aircraft Scheduling Problem (ASP) deals with the scheduling of aircraft on parallel runways. Each aircraft has its weight penalty and can operate on a runway when ready Zhang et al. [4]. The actual operation time cannot be before the ready time and after the deadline. This time should be as close as possible to the target time of the aircraft Yang et al. [5]. It is known as the time window from the ready time to the deadline. It is impossible to deviate from the deadline. The aircraft in question is not assigned to the runway and the scheduling is known as infeasible if the aircraft operation time exceeds the deadline Shakibayifar et al. [6]. The target time can be predetermined, but the operation time depends entirely on the landing or take-off conditions. Thus, an aircraft may not be able to land or take-off at or near its target time Çiftçi and Özkır [7]. Priority is given to landing rather than take-off, and priority is also given to large aircraft Zhang et al. [4]. Besides, the required separation time between the aircraft in question and other aircraft must be considered. Separation time is considered to prevent the risk of landing or take-off disturbances Sama et al. [8]. When landing or taking off, each aircraft produces turbulence that causes scheduling disturbances. This turbulence varies depending on the type of operation and the size of the aircraft Sama et al. [8]. Hence, the problems of scheduling in this area fall into two general categories: 1) airline problems including fleet, passenger, crew and flight crew allocation, and aircraft maintenance. 2) Problems related to take-off and landing restrictions on one runway to take-off and landing on different runways on the one hand and restrictions such as aircraft size, number of passengers, emergency landing, maintenance and failure of runways, weather conditions, etc. which take the problem out of its initial state and disrupt the initial schedule. Hence, a rescheduling based on the new conditions is required. Some studies focus on different heuristic algorithms and methods for expressing flight schedules due to the complexity of aircraft landing and take-off. Esmaeilidouki et al. [9] solved a problem of routing and transporting hazardous materials. They used a Genetic Algorithm (GA) to pay attention to the time of transportation and routing of materials.



Simultaneously with other parts of the world, flight scheduling in Iran seems necessary due to the dynamics of distance scheduling due to the increase in flights and, consequently, the expansion of flight-related problems on the one hand and the impossibility of developing airport runways in the short term and the high cost of these projects on the other hand. Moreover, constraints such as accessible runway, adverse weather conditions, emergency landing, fuel shortages, security accidents, the unpredictability of flight during landing in general and for Iranian airports in particular, waste of time for cargo delivery, delays and crowds on departure, and the proximity of Iranian airports to major cities that cause problems for residents near airports such as air pollution, noise pollution, etc. and cause the impossibility of flying at night or incurring additional costs for distance travel, etc. make it necessary to pay attention to flight schedules under conditions of uncertainty.

Finally, in Iranian airports, including Tehran airport, problems such as a wide flight range can be mentioned, which has caused the average flight time to be unreasonably extended. On the other hand, problems such as aircraft idle times can be mentioned. The airport would have achieved better quality for both flight and customer service if there was a proper flight schedule. Thus, the main problem of

this study is to develop a model for scheduling the time interval between flights so that more benefits and lower costs are achieved. In this study, an attempt has been made to provide a regular schedule taking into account the dynamic conditions at Tehran airport using scientific methods. In this way, improvements can be expected in various areas such as time interval scheduling, robust scheduling, attention to various components, time and cost savings, and so on.

## 2 | Literature Review

Airlines play an important role in transportation today, and air transportation has a major share of transportation Salehipour et al. [10]. As demand for air transportation grows rapidly, global air traffic is expected to double over the next 15 years. It is even expected to triple in some places. Many large airports are at high risk of air traffic delays or will be soon Zhou et al. [11]. The first idea to solve this problem is to increase the capacity of airports, however, this has also become a major problem Arkind [12]. In the current airport system, runways are considered the primary bottleneck at the airport Idris et al. [13]. Because the landing and take-off of all aircraft depend on the condition of the runways. So, it can be argued that a slight increase in runway efficiency significantly increases the efficiency of the airport. Many researchers have focused on the runway system, and one of the most important operational problems is the ASP. This problem tries to make the most of the runway by scheduling the aircraft landing and take-off as much as possible in a predetermined interval.

With the passage of the Air Transport Liberalization Act in 1978, the way was paved for fundamental changes in the aviation industry Sinha [14] so that airlines could determine the flight route and ticket price of each route themselves. This created a competitive environment between airlines Sama et al. [15]. Today, according to forecasts, demand for aviation is expected to grow at an annual rate of 3% to 5%, despite the recent recession. Therefore, increased traffic causes high obstruction in the terminal areas and delays in the arrival of aircraft and creates long queues in cargo departure areas Fernandes et al. [16].

In this way, total air traffic is steadily increasing, and the number of commercial aircraft used will double over the next two decades Lieder and Stolletz [17]. Matching more flights is a significant challenge given the current level of transportation at busy airports. Runway capacity is often a limiting factor that creates plans to offer additional flights at the airport. Also, the allocation of the fleet has its costs and rules, which are mentioned below. As such, airlines are forced to use powerful tools to make informed decisions, reduce costs, and increase their share of existing demand to survive and establish themselves in a competitive market. One of these tools is the use of systematic scheduling approaches based on mathematical logic in different sectors of airlines. One of the main factors affecting the use of runways is the implementation of the minimum separation between aircraft landing, which is rooted in safety considerations Lee et al. [18]. Wave vortices are circulating air masses that are produced as a result of the flight. These vortices can be dangerous for one aircraft below another. The vortices generated by larger aircraft are stronger but they will not affect the safe operation of the aircraft if the aircraft is at a reasonable distance from another. Besides, if the lower aircraft is lighter than the upper, these vortices will have a greater impact on the lighter aircraft. Therefore, the minimum required distance between aircraft depends on the weight of the upper and lower aircraft. As a result, effective scheduling will help prevent lighter aircraft from landing immediately after a heavier aircraft lands or takes off at Zhou et al. [11].

Flight scheduling is a major part of an airline's operations because a variety of factors must be considered in developing a schedule, and flight operations must be highly safe and reliable. Developing a flight schedule or sub-schedule usually consists of a reciprocating process. This process is very time-consuming to reach an operational flight schedule and is usually done over six months Fernandes et al. [16]. In addition to the safety issues that are the responsibility of air traffic control, other stakeholders are very interested in how the landing is scheduled. The downside is the concern for airlines and airports. Airport operations, such as missions to patrol and carry passengers' luggage, require careful scheduling, and delays in a landing may have detrimental effects on similar operations for subsequent aircraft. Airlines prefer schedules that minimize fuel costs Zhang et al. [4]. In studies by Allahverdi et al. [19] and Ball et al. [20], different problem-

solving approaches and objective functions were reviewed in the literature related to flight schedules. In particular, the main objective functions include minimizing delays and costs. Costs are calculated based on deviations from the nominal schedule in terms of delays. Regarding the arrival schedule, Zhan et al. [21] predicted and assigned the sum of the differences between the landing times of each aircraft. Sama et al. [15] limited aircraft delays and deviations from the timetable by considering aviation priorities (aviation priorities refer to the classification of aircraft for a flight on the runway. For example, international aircraft are given priority due to the importance of on-time flights, and domestic flights are next). Khaksar and Sheikholeslami [22] presented a method for airline delay prediction via machine learning algorithms based on data mining, random forest Bayesian classification, K-means clustering, and hybrid approach and calculated delay occurrence and magnitude in both Iran and USA networks. In a study by Beasley et al. [23], the problem of aircraft displacement was investigated by considering transportation costs using the distance-to-cost adjustment approach. In particular, additional penalties should be considered if the aircraft is delayed concerning the initial solution. Bennel et al. [24] allocated landing times for aircraft based on the evaluation of a specific route by minimizing flight time and using routing patterns by maximizing the minimum time between two landings. Hu and Di Paolo [25] considered two objective functions: minimizing the delay of all aircraft and maximizing the length of all arrival queues. The first objective function emphasizes the operating cost of the aircraft, but the second objective function emphasizes the objective functions, which focus on the efficiency of using the airport capacity. Bennell et al. [26] examined the dynamic landing schedule at a single-runway airport. They considered the time window limit for each landing time and the minimum separation distance between successive landings where the separation time depends on the weight classes of the two aircraft at landing. The multi-objective formula was proposed.

According to runway capacity, delays and fuel costs due to aircraft maneuvering, and additional flight time to reach the landing schedule. Kenan et al. [27] investigated the landing and take-off schedules of aircraft in terms of runway interdependencies and their heterogeneity and proposed an optimization method for the flight scheduling problem with general runway configurations (it is the runway that is used by 80% of flights, and there are some dedicated runways for private or military aircraft or giant aircraft). Cheng et al. [28] introduced the concept of flight operation risk assessment system for an airline and discussed the correlation between a risk factor and its sub components with fuzzy inference system. They also developed algorithms to identify the critical risk factors based on sensitivity of the risk factor and heuristic search.

Kim et al. [29] developed a mathematical model to provide a basis for planning airport facilities and increasing existing services in Incheon International Airport. It was found that the proposed model has good prediction capability for traffic volume on the Incheon International Airport Expressway on an hourly basis.

Tavakkoli Moghaddam et al. [30] considered the issue of aircraft meeting scheduling as a single band and solved it using a fuzzy planning approach. In their work, they proposed methods for the problem of aircraft landing with the shortest waiting time in the desired time window in critical situations, such as the closest landing time to the target time for each aircraft or the minimum landing time of aircraft.

Rashidi Komijan et al. [31] present a mathematical model for an integrated airline fleet assignment and crew scheduling. They use Vibration Damping Optimization (VDO) algorithm to an appropriate solution to their problem during a reasonable time period. An experimental design based on the Taguchi method was taken into account too. In the discussion of solution methods. Hassanpour et al. [32] present a robust bi-level programming model for designing a closed-loop supply chain and use a robust bi-level and GA for solve the problem.

The landing and take-off of each aircraft must be assigned to a runway or time. However, the requirements for separating two aircraft are met depending on the aircraft tail and minimizing the cost of delays. Some runways can only be used for landing, take-off, or certain types of aircraft. At the same

time, additional separation restrictions should be considered in scheduling airport runways. The dynamic scheduling approach presented in this study solves realistic examples of the problem for optimization in short computation time. Moreover, this study proposes a scheduling horizon for large examples that give near-optimal results. Therefore, in a comprehensive flight schedule, the modeling process is complex and difficult due to the large size of the problem, the types of constraints, the types of objective functions to be optimized, the parameters, and the types of decision variables. This is why researchers divide the problem into several smaller, independent problems and then solve each one separately.

The main problems proposed in the flight schedule are as follows:

I. Aircraft landing and take-off schedule design.
II. Fleet al.location to flight.
III. Determining the flight path and aircraft maintenance schedule (allocation of aircraft to flight).
IV. Flight crew scheduling.

However, each of the more detailed problems needs to be optimized in each of the sub-problems. The flight scheduling problem, which covers all sub-problems, will not necessarily be optimal if the optimal solution for each sub-problem is discrete. In addition to the problem, in such a case, there is still a reciprocating process between each of the sub-problems, especially with the first stage, the landing and take-off schedule, so that the flight schedule is in a relatively optimal state, which will waste a lot of time. Therefore, adopting a different approach that considers all sub-problems as discrete can provide a more optimal solution to the flight scheduling problem and significantly reduce the time interval of the scheduling process. So, it seems necessary to adopt such an approach.

In this study, a robust mathematical model is designed and solved for the problem of optimal scheduling of passenger aircraft flight time interval at Tehran airport.

## 3 | Mathematical Modeling

The ASP is to determine the optimal sequence of landing or take-off and assigning them to different and same runways, taking into account the limitations of parking spaces so that the total cost of flight delays is minimized. In other words, the ASP deals with the scheduling of aircraft on parallel runways. Hence, the modeling assumptions are as follows:

I. The departure time of each aircraft depends on their sequence on the runway.
II. Each runway can direct a maximum of one aircraft at any moment.
III. Each aircraft can take-off or land on a maximum of one runway at any moment.
IV. Runways are not continuously available.
V. All flight times are as robust uncertainty.

**Indices**

- *i: runway*
- *j: aircraft (j)*
- *l: aircraft (l)*
- *t: time interval*

**Input parameters**

n: the number of flights.

$m^t$: the number of ready runways in each period t.

$d_j$: The flight time of aircraft j.

$P_{il}$: The flight duration of aircraft l on the runway i.

$r_j$: Access time for aircraft j to start the take-off process.

$\alpha_j$: Cost of haste in the landing/take-off of aircraft j.

$\beta_j$: Cost of delays in landing/take-off of aircraft j.

$M_{ij}^t$t: If it were possible for aircraft j to fly or land on runway i in period t, 1, and, otherwise, 0.

$S_{jl}^t$: The ready time for aircraft l when ready to fly/land on one of the runways after aircraft j in step t.

$ch_{il}^t$: The ready time for aircraft l when the first aircraft to take off or land on runway i in stage t.

$av_i^t$: The time to access runway i in period t.

$pd_j^t$ : The probability of runway disturbances after landing/take-off of aircraft j in period t.

$R^t$: The time required to repair the runway in each period t.

$M'$: A large positive integer number.

**Decision variables**

$X_{ij}^t$: If aircraft j flies/lands on runway i in period t, 1, and, otherwise, 0.

$Y_{ijl}^t$: If aircraft j flies/lands on runway i in period t before aircraft l, 1, and, otherwise, 0.

$C_j^t$: The time to complete the flight of aircraft j in period t.

$C_l^t$: The time to complete the flight of aircraft l in period t.

$E_j$: The haste time of aircraft j for landing/take-off.

$T_j$: The delay time of aircraft j for landing/take-off.

The model variables including E, C, and T have non-negative integers, and variables X and Y have values of zero and one.

## 3.1 | Decision Variables

$$\text{Min C} = \sum_{j=1}^{n} \alpha_j E_j + \beta_j T_j.$$

The objective function of the model is equal to the sum of the acceleration and delay times of the flights. In this formula, the values of the decision variables Ej and Tj for j-type aircraft are obtained from *Eqs. (1)* and *(2)*, respectively.

$$E_j = \max\left(0, d_j - C_j^t\right), \quad (1)$$
$$T_j = \max\left(0, C_j^t - d_j\right), \quad (2)$$

Tohidi Nasab et al. | Int. J. Res. Ind. Eng. 12(1) (2023) 21-42

$$\sum_{I=1}^{m^t} X_{ij}^t = 1 \quad \text{for all } t, j, \tag{3}$$

$$\sum_{l=1}^{n} Y_{ijl}^t \leq X_{ij}^t \quad \text{for all } i, j, t \quad j \neq 1, \tag{4}$$

$$\sum_{j=0}^{n} Y_{ijl}^t = X_{il}^t \quad \text{for all } t, i, l \quad l \neq j, \tag{5}$$

$$\sum_{l=1}^{n} Y_{i0l}^t = 1 \quad \text{for all } t, i, \tag{6}$$

$$X_{ij}^t \leq M_{ij}^t \quad \text{for all } t, i, j, \tag{7}$$

$$C_l^t - C_j^t \geq S_{jl}^t + P_{il} * Y_{ijl}^t + pd_j^t * R^t + \left(Y_{ijl}^t - 1\right) * M \quad \text{for all } t, \imath, \jmath, l, \tag{8}$$

$$C_j^t \geq 0 \quad \text{for all } t, j, \tag{9}$$

$$C_l^t - C_l^{t-1} \geq \sum_{i=1}^{m^t} \sum_{j=1}^{n} Y_{ijl}^t * S_{jl}^t + \sum_{i=1}^{m^t} ch_{il}^t * Y_{i0l}^t + \sum_{i=1}^{m^t} \sum_{j=1}^{n} P_{il} * Y_{ijl}^t + \sum_{i=1}^{m^t} P_{il} * Y_{i0l}^t + \sum_{i=1}^{m^t} \sum_{j=1}^{n} pd_j^t * R^t * Y_{ijl}^t \quad \text{for all } t, l \quad j \neq l, \tag{10}$$

$$C_l^t \geq \sum_{i=1}^{m^t} av_i^t * Y_{i0l}^t + \sum_{i=1}^{m^t} ch_{il}^t * Y_{i0l}^t + \sum_{i=1}^{m^t} P_{il} * Y_{i0l}^t \quad \text{for all } t, l, \tag{11}$$

$$C_j^0 \geq r_j \quad \text{for all } j, \tag{12}$$

$$T_j \geq C_j^t - d_j \quad \text{for all } t, j, \tag{13}$$

$$T_j \geq 0 \quad \text{for all } j, \tag{14}$$

$$E_j \geq d_j - C_j^t \quad \text{for all } t, j, \tag{15}$$

$$E_j \geq 0 \quad \text{for all } j. \tag{16}$$

## 3.2 | The Limitations of the Proposed Model

*Constraint (3)* indicates that each aircraft can land/take off on one and only one runway in each period t. *Constraints (4)* and *(5)* ensure that each aircraft has a landing/take-off operation immediately before and after only one other aircraft on the runway in each period t. *Constraint (6)* specifies the first flight on runway i in each period t. *Constraint (7)* introduces limited access to the runway. As stated in the model input parameters section, if aircraft j can fly/land on runway i in period t, the value of parameter $M_{ij}^t$ will be 1. Otherwise, it will be 0. The possibility of flight/landing of aircraft j on runway i in period t is determined according to the movement set of aircraft j, i.e. $M_j^t$, which is a subset of runways $M^t$ and includes all runways on which aircraft j can land/take off. This constraint, thus, constrains the model to consider $M_{ij}^t$, which is one of the input parameters of the model, for assigning runway i to aircraft j and, consequently, assigning the value of 1 to the decision variable $X_{ij}^t$. This assignment is made if the value of $M_{ij}^t$ is 1 such as $X_{ij}^t$. *Constraint (8)* ensures that the landing/take-off time of the aircraft is the result of the time it takes for the aircraft to be ready for flight, the duration of flight on the runway, and the likelihood of flight disturbances. *Constraint (9)* ensures that the flight time starts from zero. *Constraint (10)* ensures that the flight schedules do not interfere with each other. *Constraint (11)* ensures that the first aircraft does not have a problem flying. *Constraint (12)* specify the completion time of each flight. *Constraints (13)* and *(14)* specify the constraints on delay times for flight j. *Constraints (15)* and *(16)* specify the constraints on haste times for flight j.

## 3.3 | Bertsimas and Sim Robust Uncertainty Approach

The robust optimization specifies a suitable uncertainty set for imprecise input data and gives a solution that ensures feasibility in all amounts of uncertain parameters within the uncertainty set Ben-Tal and Nemirovski [33].

According to the evaluation, uncertainty in the flight time is added to the model using robust scheduling and the Bertsimas and Sim approach. With this change, *Constraint (8)* is modified as the Bertsimas model. Therefore, the proposed model is linear. Studies show that flight time is one of the important parameters whose values may exceed the nominal values. As a result, considering this parameter in uncertainty conditions can bring the proposed model closer to the reality of the problem. Robust scheduling and the Bertsimas and Sim approach are used to consider uncertainty in the flight time. Robust optimization seeks

optimal or near-optimal solutions that are likely to be feasible. The Bertsimas and Sim approach is one of the four main approaches for considering uncertainty in robust scheduling. This section briefly mentions this approach. For this purpose, the following linear programming model is considered.

$$\begin{aligned}&\mathrm{Min}\ \sum_j c_j x_j,\\&\mathrm{s.t.}\\&Ax \le b.\end{aligned} \tag{17}$$

In this model, it is assumed that only the right-hand coefficients in the constraints, matrix A, have uncertain values, and the values of this matrix, i.e. $a_{ij}$, fluctuate in the range $[\tilde{a}_{ij} - \hat{a}_{ij}, \tilde{a}_{ij} + \hat{a}_{ij}]$, where $\tilde{a}_{ij}$ and $\hat{a}_{ij}$ are the nominal values and the maximum deviation of parameter $a_{ij}$, respectively. The proposed Bertsimas and Sim robust model is as follows:

$$\begin{aligned}&\min \sum_j c_j x_j,\\&\mathrm{s.t.}\\&\sum_j \tilde{a}_{ij} x_j + z_i \Gamma_i + \sum_{j \in J_i} \mu_{ij} \le b_i \quad \text{for all } i,\\&z_i + \mu_{ij} \ge \hat{a}_{ij} x_{ij} \quad \text{for all } i, j,\\&z_i, \mu_{i,j} \ge 0 \quad \text{for all } i, j,\end{aligned} \tag{18}$$

where $z_i$ and $\mu_{ij}$ are dual auxiliary variables, and parameter $\Gamma_i$, called the uncertainty budget, indicates the level of conservatism that is chosen according to the importance of the constraint as well as the risk-taking of the decision-maker. Hence, *Constraints (8)*, *(10)* and *(11)* become *Constraints (19)* to *(22)* according to the Bertsimas and Sim robust model.

$\hat{p}_{il}$: The tolerance of flight time of aircraft l on runway i.

$\Gamma_{il}$: The uncertainty budget for flight time.

**Variables**

$pp_{il}$ and $q_{ilt}$: The robust model variables.

$$C_l^t - C_j^t \ge S_{jl}^t + P_{il} * Y_{ijl}^t + \Gamma_{il} pp_{il} + q_{ilt} + pd_j^t * R^t + \left(Y_{ijl}^t - 1\right) * M \quad \text{for all } t, i, j, l, \tag{19}$$

$$C_l^t - C_l^{t-1} \ge \sum_{i=1}^{m^t} \sum_{j=1}^{n} Y_{ijl}^t * S_{jl}^t + \sum_{i=1}^{m^t} ch_{il}^t * Y_{i0l}^t + \sum_{i=1}^{m^t} \sum_{j=1}^{n} P_{il} * Y_{ijl}^t + \sum_{i=1}^{m^t} P_{il} * Y_{i0l}^t + \Gamma_{il} pp_{il} + q_{ilt} + \sum_{i=1}^{m^t} \sum_{j=1}^{n} pd_j^t * R^t * Y_{ijl}^t \quad \text{for all } t, l \quad j \ne l, \tag{20}$$

$$C_l^t \ge \sum_{i=1}^{m^t} av_i^t * Y_{i0l}^t + \sum_{i=1}^{m^t} ch_{il}^t * Y_{i0l}^t + \sum_{i=1}^{m^t} P_{il} * Y_{i0l}^t + \sum_{i=1}^{m^t} P_{il} * Y_{i0l}^t + \Gamma_{il} pp_{il} + q_{ilt} \quad \text{for all } t, l, \tag{21}$$

$$pp_{il} + q_{ilt} \ge \hat{p}_{il} * Y_{i0l}^t \quad \text{for all } i, l, t. \tag{22}$$

## 4 | Funding

In this section, the proposed mathematical model is validated. The collected data indicate that the movement position of the aircraft does not follow the same distribution functions. The status of the mathematical model parameters is as follows based on the timing performed.



Tohidi Nasab et al. | Int. J. Res. Ind. Eng. 12(1) (2023) 21-42

## 4.1 | Aircraft Ready Time

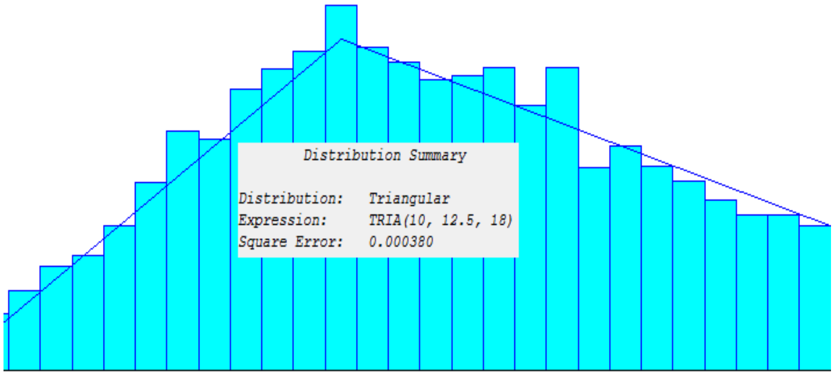


**Fig. 1. Aircraft ready time on the runway.**

The ready time parameter of aircraft j when selected as the first aircraft.

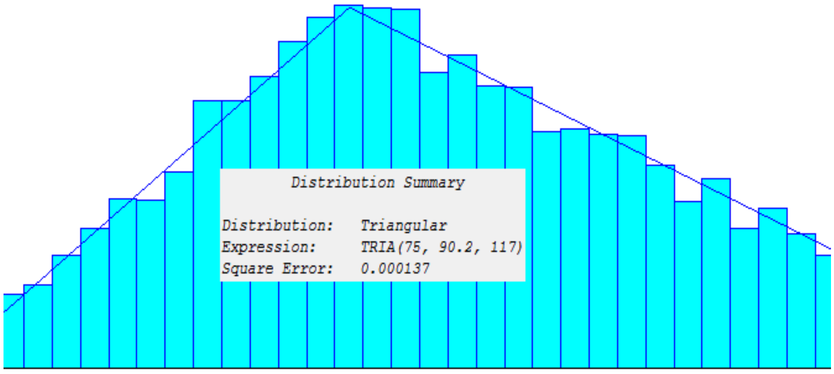


**Fig. 2. Aircraft's ready time when selected as the first aircraft.**

According to the evaluation, the aircraft's ready time for landing and flight follows the triangular function with a minimum value of 10 minutes and a maximum value of 18 minutes, which is coded based on the obtained values of the mathematical model.

The ready time parameter of aircraft j when selected as the first aircraft.

**Table 1. Adjustment of the mathematical model parameters.**

| The Mathematical Model Parameters | Intended Values |
|---|---|
| The flight time of aircraft j | U~ [10,30] |
| The flight time of aircraft j on the runway | U~ [1,3] |
| The time to access aircraft j to start the take-off process | U~ [1,6] |
| The cost of hastening the landing/take-off | U~ [20,50] $ |
| The cost of Delays in landing/take-off | U~ [80,100] $ |
| The possibility of runway disturbances after landing/takeoff | 0.35 |

According to the adjustment of the mathematical model parameters, the flight schedule of one of the airports is considered as follows (it is worth mentioning that small, medium, and large runways are selected for the schedule. Therefore, 20 aircraft are investigated in 3 runways over a 24-hour schedule. The flight schedule is as follows:

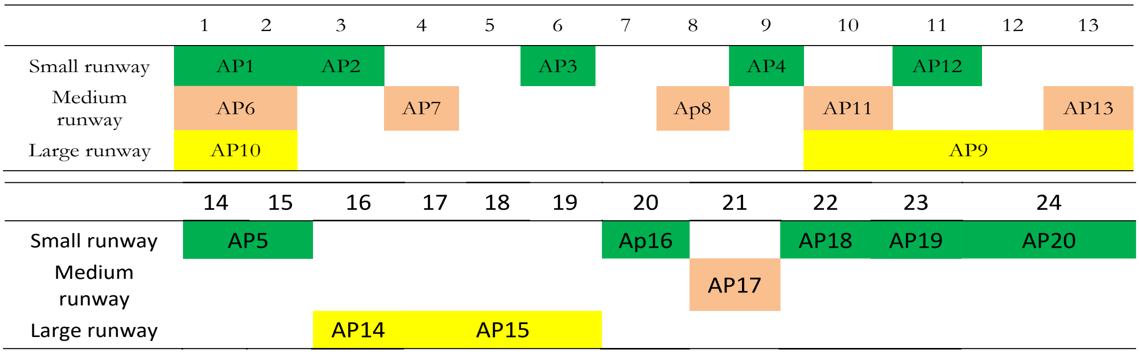


**Fig. 3. The flight schedule for 24 hours.**

The evaluation of the designed problem and flight time of the aircraft show that 50% of the aircraft fly on small runways, 30% on medium runways, and 20% on large runways. The flight schedule for 24 hours is shown in *Fig 3*. Since the problem under study is NP-HARD, in this section, the mathematical model is evaluated using genetic meta-heuristic and imperialist competitive algorithms.

## 4.2 | Adjusting the Meta-Heuristic Algorithm Parameters

One of the most important steps in designing meta-heuristic algorithms to achieve optimal solutions is algorithm calibration. Different values of control parameters of these algorithms may affect computation indices including solution quality and computation time, so a series of calibration tests are often performed to find the optimal combination of different values of algorithm control parameters. The algorithms proposed in this study are genetic and imperialist competitive algorithms. GA control parameters include initial population size ($Pop_{GA}$), crossover rate ($P_c$), mutation rate ($P_m$), and the maximum number of generations ($G_{max}$). The imperialist competitive algorithm control parameters are the number of neighborhoods produced ($Pop_{ICA}$), the number of iterations (Decade), and the percentage effect of the total power of each imperial colony on its power (PICA). Each of these parameters affects the computation indices in a certain range of their values and has a negligible effect outside this range. The computation indices used in the tests of this section and future sections are the mean values of the objective function for the optimal solutions and their mean computation times per ten iterations of the algorithm. A set of tests based on the Taguchi method is designed to investigate the interaction of control parameters of the proposed algorithms and achieve their optimal combination. Each of the parameters for each of the proposed algorithms in the previous section is tested at three levels. Solution levels are the mean solutions obtained and the mean computation times. To simultaneously consider the quality of solutions and computation times, the values of the two are normalized and added together. First the parameters of the GA and then the parameters of the Imperialistic Competitive Algorithm (ICA) algorithm were examined. *Table 2* shows the desired factors and their levels for the GA. The tests required to examine the various combinations of factors and the corresponding solutions can be seen in *Table 3*. The generated data are analyzed by MINITAB 14 software, and the results are provided in the following tables.

**Table 2. Factors and their levels.**

| Factor | Levels |
|---|---|
| $Pop_{GA}$ | 200, 300, 400 |
| $P_c$ | 0.8, 0.7, 0.6 |
| $P_m$ | 0.15, 0.12, 0.10 |
| $G_{max}$ | 200, 300, 400 |
| $P_{mu}$ | 0.10, 0.15, 0.2 |

To simultaneously examine the effect of factors on the quality of solutions and computation times, their values are normalized, added together, and become a solution variable. Finally, the inverse of this value is calculated and considered as the solution variable. The larger the value, the better. This can be seen in *Table 4*.

**Table 3. Combinations of factors and corresponding solution levels in multifactorial tests.**

| $Pop_{GA}$ | $P_c$ | $P_m$ | $P_{mu}$ | $G_{max}$ | Solution | CPU(s) |
|---|---|---|---|---|---|---|
| 200 | 0.6 | 0.10 | 0.10 | 200 | 164.00 | 6.56 |
| 200 | 0.6 | 0.10 | 0.10 | 300 | 42.00 | 11.80 |
| 200 | 0.6 | 0.10 | 0.10 | 400 | 46.70 | 13.73 |
| 200 | 0.7 | 0.12 | 0.15 | 200 | 40.00 | 8.50 |
| 200 | 0.7 | 0.12 | 0.15 | 300 | 13.67 | 12.60 |
| 200 | 0.7 | 0.12 | 0.15 | 400 | 32.33 | 13.75 |
| 200 | 0.8 | 0.15 | 0.20 | 200 | 66.33 | 12.45 |
| 200 | 0.8 | 0.15 | 0.20 | 300 | 26.33 | 16.58 |
| 200 | 0.8 | 0.15 | 0.20 | 400 | 27.00 | 20.70 |
| 300 | 0.6 | 0.12 | 0.20 | 200 | 20.67 | 14.17 |
| 300 | 0.6 | 0.12 | 0.20 | 300 | 14.33 | 23.07 |
| 300 | 0.6 | 0.12 | 0.20 | 400 | 48.33 | 12.80 |
| 300 | 0.7 | 0.15 | 0.10 | 200 | 20.33 | 16.21 |
| 300 | 0.7 | 0.15 | 0.10 | 300 | 21.67 | 22.89 |
| 300 | 0.7 | 0.15 | 0.10 | 400 | 44.67 | 13.21 |
| 300 | 0.8 | 0.10 | 0.15 | 200 | 18.67 | 22.58 |
| 300 | 0.8 | 0.10 | 0.15 | 300 | 22.33 | 23.54 |
| 300 | 0.8 | 0.10 | 0.15 | 400 | 49.10 | 12.51 |
| 400 | 0.6 | 0.15 | 0.15 | 200 | 15.00 | 28.12 |
| 400 | 0.6 | 0.15 | 0.15 | 300 | 45.20 | 14.30 |
| 400 | 0.6 | 0.15 | 0.15 | 400 | 26.57 | 20.01 |
| 400 | 0.7 | 0.10 | 0.20 | 200 | 14.87 | 27.95 |
| 400 | 0.7 | 0.10 | 0.20 | 300 | 14.65 | 27.80 |
| 400 | 0.7 | 0.10 | 0.20 | 400 | 13.00 | 29.14 |
| 400 | 0.8 | 0.12 | 0.10 | 200 | 8.60 | 34.00 |
| 400 | 0.8 | 0.12 | 0.10 | 300 | 9.20 | 31.23 |
| 400 | 0.8 | 0.12 | 0.10 | 400 | 7.60 | 31.46 |

**Table 4. Combinations of factors and normalized solution levels in multifactorial tests.**

| $Pop_{GA}$ | $P_c$ | $P_m$ | $P_{mu}$ | $G_{max}$ | Normalized | 1/Normalized |
|---|---|---|---|---|---|---|
| 200 | 0.6 | 0.10 | 0.10 | 200 | 0.200401 | 4.99 |
| 200 | 0.6 | 0.10 | 0.10 | 300 | 0.070722 | 14.14 |
| 200 | 0.6 | 0.10 | 0.10 | 400 | 0.079804 | 12.53 |
| 200 | 0.7 | 0.12 | 0.15 | 200 | 0.062105 | 16.10 |
| 200 | 0.7 | 0.12 | 0.15 | 300 | 0.039810 | 25.12 |
| 200 | 0.7 | 0.12 | 0.15 | 400 | 0.063385 | 15.78 |
| 200 | 0.8 | 0.15 | 0.20 | 200 | 0.099832 | 10.02 |
| 200 | 0.8 | 0.15 | 0.20 | 300 | 0.061938 | 16.15 |
| 200 | 0.8 | 0.15 | 0.20 | 400 | 0.070604 | 14.16 |
| 300 | 0.6 | 0.12 | 0.20 | 200 | 0.050836 | 19.67 |
| 300 | 0.6 | 0.12 | 0.20 | 300 | 0.060636 | 16.49 |
| 300 | 0.6 | 0.12 | 0.20 | 400 | 0.079888 | 12.52 |
| 300 | 0.7 | 0.15 | 0.10 | 200 | 0.054357 | 18.40 |
| 300 | 0.7 | 0.15 | 0.10 | 300 | 0.068697 | 14.56 |
| 300 | 0.7 | 0.15 | 0.10 | 400 | 0.076483 | 13.07 |
| 300 | 0.8 | 0.10 | 0.15 | 200 | 0.064667 | 15.46 |
| 300 | 0.8 | 0.10 | 0.15 | 300 | 0.070699 | 14.14 |
| 300 | 0.8 | 0.10 | 0.15 | 400 | 0.080214 | 12.47 |
| 400 | 0.6 | 0.15 | 0.15 | 200 | 0.071084 | 14.07 |
| 400 | 0.6 | 0.15 | 0.15 | 300 | 0.079179 | 12.63 |
| 400 | 0.6 | 0.15 | 0.15 | 400 | 0.068788 | 14.54 |
| 400 | 0.7 | 0.10 | 0.20 | 200 | 0.070609 | 14.16 |
| 400 | 0.7 | 0.10 | 0.20 | 300 | 0.070070 | 14.27 |
| 400 | 0.7 | 0.10 | 0.20 | 400 | 0.070749 | 14.13 |
| 400 | 0.8 | 0.12 | 0.10 | 200 | 0.075026 | 13.33 |
| 400 | 0.8 | 0.12 | 0.10 | 300 | 0.070403 | 14.20 |
| 400 | 0.8 | 0.12 | 0.10 | 400 | 0.069012 | 14.49 |

**Table 5. Estimated correlation coefficients of the model for SN ratios.**

| Term | Coef | SE Coef | T | P |
|---|---|---|---|---|
| Constant | 22.9674 | 0.4156 | 55.270 | 0.000 |
| $Pop_{GA}$200 | -0.4973 | 0.5877 | -0.846 | 0.410 |
| $Pop_{GA}$300 | 0.5624 | 0.5877 | 0.957 | 0.353 |
| $P_c$ 0.6 | -0.8177 | 0.5877 | -1.391 | 0.043 |
| $P_c$ 0.7 | 1.0433 | 0.5877 | 1.775 | 0.025 |
| $P_m$ 0.10 | -1.1060 | 0.5877 | -1.882 | 0.038 |
| $P_m$0.12 | 1.1476 | 0.5877 | 1.953 | 0.0۲9 |
| $P_{mu}$ 0.12 | -0.9031 | 0.5877 | -1.537 | 0.144 |
| $P_{mu}$ 0.15 | 0.7053 | 0.5877 | 1.200 | 0.248 |
| $G_{max}$200 | -0.5723 | 0.5877 | -0.974 | 0.345 |
| $G_{max}$300 | 0.8050 | 0.5877 | 1.370 | 0.009 |

Factor correlation coefficients for SN ratios are presented in *Table 5*. Coefficients with larger absolute values are more important than other factors. These coefficients are used to rank the factors in the solution table. As can be seen in the table, the factors $P_c = 0.6$, $P_m = 0.10$, $P_{mu} = 0.12$, and $G_{max} = 300$ have a significant effect on the solutions at the 95% confidence level.

**Table 6. Analysis of variance for SN ratios.**

| Source | DF | Seq SS | Adj SS | Adj MS | F | P |
|---|---|---|---|---|---|---|
| $Pop_{size}$ | 2 | 5.110 | 5.110 | 2.555 | 0.55 | 0.589 |
| $P_c$ | 2 | 16.272 | 16.272 | 8.136 | 1.75 | 0.016 |
| $P_m$ | 2 | 22.877 | 22.877 | 11.439 | 2.45 | 0.018 |
| $P_{mu}$ | 2 | 12.170 | 12.170 | 6.085 | 1.31 | 0.299 |
| $G_{max}$ | 2 | 9.267 | 9.267 | 4.633 | 0.99 | 0.029 |
| Residual Error | 14 | 74.599 | 74.599 | 4.662 | | |
| Total | 24 | 140.296 | | | | |

Similar results are presented in *Table 7*, which shows the factor correlation coefficients for the mean solutions. Moreover, the analysis of variance for the SN coefficient and the mean solutions are performed for the tested factors, and the results are given in *Tables 6* and *8*. According to the analysis of variance, the factors $P_m$ , $P_c$ and $G_{max}$with a p-value of less than 0.05 have a significant effect on the solutions as expected.

**Table 7. Estimated correlation coefficients of the model for mean solutions.**

| Term | Coef | SE Coef | T | P |
|---|---|---|---|---|
| Constant | 14.5035 | 0.3741 | 38.765 | 0.000 |
| $Pop_{GA}$200 | -0.1711 | 0.8344 | -0.205 | 0.840 |
| $Pop_{GA}$300 | 0.6944 | 0.8344 | 0.832 | 0.417 |
| $P_c$ 0.6 | -0.9944 | 0.8344 | -1.192 | 0.251 |
| $P_c$ 0.7 | 1.6733 | 0.8344 | 2.006 | 0.042 |
| $P_m$ 0.10 | -1.5822 | 0.8344 | -1.896 | 0.016 |
| $P_m$0.12 | 1.9078 | 0.8344 | 2.287 | 0.036 |
| $P_{mu}$ 0,1 | -1.2022 | 0.8344 | -1.441 | 0.169 |
| $P_{mu}$0.15 | 1.0867 | 0.8344 | 1.302 | 0.211 |
| $G_{max}$ 200 | -0.4811 | 0.8344 | -0.577 | 0.042 |
| $G_{max}$300 | 1.2411 | 0.8344 | 1.487 | 0.000 |

**Table 8. Analysis of variance for mean solutions.**

| Source | DF | Seq SS | Adj SS | Adj MS | F | P |
|---|---|---|---|---|---|---|
| $Pop_{GA}$ | 2 | 7.069 | 7.069 | 3.534 | 0.38 | 0.692 |
| $P_c$ | 2 | 38.249 | 38. | 19.124 | 2.03 | 0.022 |
| $P_m$ | 2 | 56.241 | 56.241 | 28.121 | 2.99 | 0.006 |
| $P_{mu}$ | 2 | 23.756 | 23.756 | 11.878 | 1.26 | 0.309 |
| $G_{max}$ | 2 | 21.145 | 21.145 | 10.572 | 1.12 | 0.001 |
| Residual Error | 14 | 150.370 | 150.370 | 9.398 | | |
| Total | 24 | 296.829 | | | | |

**Table 9. SN ratio solution.**

| Level | $Pop_{size}$ | $P_c$ | $P_m$ | $P_{mu}$ | $G_{max}$ |
|---|---|---|---|---|---|
| 1 | 22.47 | 22.15 | 21.86 | 22.06 | 22.40 |
| 2 | 23.53 | 24.01 | 24.12 | 23.67 | 23.77 |
| 3 | 22.90 | 22.74 | 22.93 | 23.17 | 22.73 |
| Delta | 1.06 | 1.86 | 2.25 | 1.61 | 1.38 |
| Rank | 5 | 2 | 1 | 3 | 4 |

Solution levels are evaluated according to mean solution indices and SN ratios, and factors are ranked to determine the priority or degree of importance of each factor. The mean solution index for each level of each factor can be seen in the solutions table. The ranking of the factors according to the solution analysis concerning SN coefficients and means can be seen in *Tables 9* and *10*. Accordingly, the $P_m$ factor has the highest rank in both tables, and the $P_c$ factor has the second rank. The ranking of other factors is the same for the mean solution indices and SN coefficients.

**Table 10. Mean solutions.**

| Level | $Pop_{size}$ | $P_c$ | $P_m$ | $P_{mu}$ | $G_{max}$ |
|---|---|---|---|---|---|
| 1 | 14.33 | 13.51 | 12.92 | 13.30 | 14.02 |
| 2 | 15.20 | 16.18 | 16.41 | 15.59 | 15.74 |
| 3 | 13.98 | 13.82 | 14.18 | 14.62 | 13.74 |
| Delta | 1.22 | 2.67 | 3.49 | 2.29 | 2.00 |
| Rank | 5 | 2 | 1 | 3 | 4 |

Factor interaction analysis is used to fine-tune the levels of factors. These effects can be seen in the following figures (*Figs. 4* and *5*).

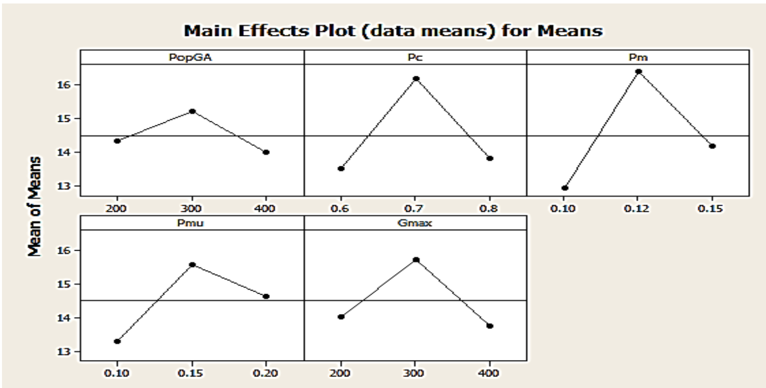


**Fig. 4. Mean solutions.**

As shown in *Fig. 4*, the mean solution index is maximized by $Pop_{GA}$ factor at level 300, by $P_c$ factor at level 0.6, by $P_m$factor at level 0.12, by $P_{mu}$ factor at level 0.15, and by $G_{max}$factor at level 300. Examining the levels of the factors in *Fig. 5* shows that the factors maximize the SN index at similar levels.

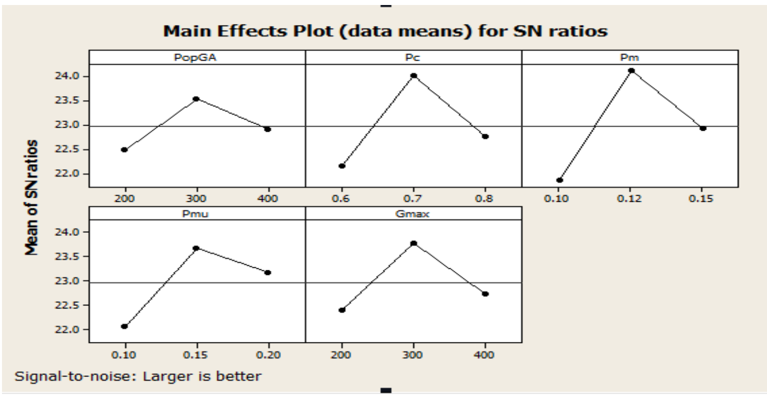


**Fig. 5. Mean SN ratio.**

Thus, the values of the control parameters of the proposed GA are adjusted according to the following table.



**Table 11. Optimal values of control parameters.**

| Factor | Levels |
|---|---|
| $Pop_{GA}$ | 300 |
| $P_c$ | 0.7 |
| $P_m$ | 0.12 |
| $P_{mu}$ | 0.15 |
| $G_{max}$ | 300 |

*Table 12* shows the factors and their levels for the imperialist competitive algorithm. The tests required to examine the various combinations of factors and the corresponding solutions are presented in *Table 13*.

**Table 12. Factors and their levels.**

| Factor | Levels |
|---|---|
| $Pop_{GA}$ | 300, 400, 500 |
| decade | 200, 300, 400 |
| $P_{ICA}$ | 0.08, 0.10, 0.12 |

**Table 13. Combinations of factors and solution levels in multifactorial tests.**

| $Pop_{ICA}$ | Decade | $P_{ICA}$ | Solution | CPU (s) |
|---|---|---|---|---|
| 300 | 200 | 0.08 | 85.2 | 0.66 |
| 300 | 200 | 0.08 | 40.6 | 0.82 |
| 300 | 200 | 0.08 | 40.2 | 1.13 |
| 300 | 300 | 0.10 | 36.0 | 0.65 |
| 300 | 300 | 0.10 | 23.0 | 0.83 |
| 300 | 300 | 0.10 | 27.8 | 1.14 |
| 300 | 400 | 0.12 | 46.2 | 0.65 |
| 300 | 400 | 0.12 | 31.4 | 0.80 |
| 300 | 400 | 0.12 | 30.8 | 1.15 |
| 400 | 200 | 0.10 | 19.0 | 1.29 |
| 400 | 200 | 0.10 | 19.0 | 1.86 |
| 400 | 200 | 0.10 | 25.6 | 0.98 |
| 400 | 300 | 0.12 | 30.6 | 1.27 |
| 400 | 300 | 0.12 | 37.8 | 1.87 |
| 400 | 300 | 0.12 | 36.2 | 0.99 |
| 400 | 400 | 0.08 | 19.0 | 1.28 |
| 400 | 400 | 0.08 | 21.8 | 1.92 |
| 400 | 400 | 0.08 | 23.0 | 0.98 |
| 500 | 200 | 0.12 | 21.4 | 2.55 |
| 500 | 200 | 0.12 | 24.6 | 1.25 |
| 500 | 200 | 0.12 | 19.0 | 1.77 |
| 500 | 300 | 0.08 | 22.6 | 2.59 |
| 500 | 300 | 0.08 | 26.0 | 1.24 |
| 500 | 300 | 0.08 | 23.4 | 1.66 |
| 500 | 400 | 0.10 | 32.2 | 2.60 |
| 500 | 400 | 0.10 | 28.2 | 1.30 |
| 500 | 400 | 0.10 | 22.6 | 1.74 |

To simultaneously examine the effect of factors on the quality of solutions and computation times, their values are normalized, added together, and become a solution variable. Finally, the inverse of this value is calculated and considered as the solution variable. The larger the value, the better. This can be seen in *Table 14*.

Tohidi Nasab et al. | Int. J. Res. Ind. Eng. 12(1) (2023) 21-42

**Table 14. Combinations of factors and normalized solution levels in multifactorial tests.**

| $Pop_{ICA}$ | Decade | $P_{ICA}$ | Normalized | 1/Normalized |
|---|---|---|---|---|
| 300 | 200 | 0.08 | 0.122624 | 8.16 |
| 300 | 200 | 0.08 | 0.072106 | 13.87 |
| 300 | 200 | 0.08 | 0.080000 | 12.50 |
| 300 | 300 | 0.10 | 0.061851 | 16.17 |
| 300 | 300 | 0.10 | 0.050734 | 19.71 |
| 300 | 300 | 0.10 | 0.065022 | 15.38 |
| 300 | 400 | 0.12 | 0.074394 | 13.44 |
| 300 | 400 | 0.12 | 0.060252 | 16.60 |
| 300 | 400 | 0.12 | 0.068981 | 14.50 |
| 400 | 200 | 0.10 | 0.058258 | 17.17 |
| 400 | 200 | 0.10 | 0.073676 | 13.57 |
| 400 | 200 | 0.10 | 0.057989 | 17.24 |
| 400 | 300 | 0.12 | 0.071981 | 13.89 |
| 400 | 300 | 0.12 | 0.097065 | 10.30 |
| 400 | 300 | 0.12 | 0.071294 | 14.03 |
| 400 | 400 | 0.08 | 0.057987 | 17.25 |
| 400 | 400 | 0.08 | 0.078742 | 12.70 |
| 400 | 400 | 0.08 | 0.054791 | 18.25 |
| 500 | 200 | 0.12 | 0.095291 | 10.49 |
| 500 | 200 | 0.12 | 0.064062 | 15.61 |
| 500 | 200 | 0.12 | 0.071241 | 14.04 |
| 500 | 300 | 0.08 | 0.097848 | 10.22 |
| 500 | 300 | 0.08 | 0.065513 | 15.26 |
| 500 | 300 | 0.08 | 0.073676 | 13.57 |
| 500 | 400 | 0.10 | 0.109924 | 9.10 |
| 500 | 400 | 0.10 | 0.069841 | 14.32 |
| 500 | 400 | 0.10 | 0.074857 | 13.36 |

**Table 15. Estimated correlation coefficients of the model for SN ratios.**

| Term | Coef | SE Coef | T | P |
|---|---|---|---|---|
| Constant | 22.5770 | 0.7015 | 32.184 | 0.000 |
| $Pop_{ICA}$300 | 0.2102 | 0.9921 | 0.212 | 0.852 |
| $Pop_{ICA}$400 | 0.5968 | 0.9921 | 0.602 | 0.009 |
| decade200 | -0.3813 | 0.9921 | -0.384 | 0.738 |
| decade300 | 0.1738 | 0.9921 | 0.175 | 0.045 |
| $P_{ICA}$0.08 | -0.5050 | 0.9921 | -0.509 | 0.661 |
| $P_{ICA}$0.10 | 0.6425 | 0.9921 | 0.648 | 0.037 |

**Table 16. Analysis of variance for SN ratios.**

| Source | DF | Seq SS | Adj SS | Adj MS | F | P |
|---|---|---|---|---|---|---|
| $Pop_{ICA}$ | 2 | 13.1550 | 13.1550 | 11.5775 | 4.79 | 0.026 |
| $Pop_{ICA}$ | 2 | 10.6559 | 10.6559 | 10.3279 | 4.22 | 0.031 |
| $P_{ICA}$ | 2 | 22.0603 | 22.0603 | 19.323 | 8.49 | 0.04 |

Factor correlation coefficients for SN ratios are presented in *Table 15*. Coefficients with larger absolute values are more important than other factors. These coefficients are used to rank the factors in the solution table. As can be seen in the table, the factors $Pop_{ICA}$ = 400, *decade* = 300, and $P_{ICA}$ = 0.1 have a significant effect on the solutions at the 95% confidence level.

Similar results are presented in *Table 17*, which shows the factor correlation coefficients for the mean solutions. Besides, the analysis of variance for the SN coefficient and the mean solutions are performed for the tested factors, and the results are given in *Tables 16* and *18*. According to the analysis of variance, the factors, $P_{ICA}$, *decade,* and $Pop_{ICA}$with a p-value of less than 0.05 have a significant effect on the solutions as expected.

Tohidi Nasab et al. | Int. J. Res. Ind. Eng. 12(1) (2023) 21-42

**Table 17. Estimated correlation coefficients of the model for mean solutions.**

| Term | Coef | SE Coef | T | P |
|---|---|---|---|---|
| Constant | 14.0996 | 0.2973 | 47.433 | 0.000 |
| $Pop_{ICA}$300 | 0.3801 | 0.4204 | 0.904 | 0.381 |
| $Pop_{ICA}$400 | 1.0132 | 0.4204 | 2.410 | 0.030 |
| decade200 | -0.4721 | 0.4204 | -1.123 | 0.280 |
| decade300 | -1.9308 | 0.4204 | -4.593 | 0.000 |
| $p_{ICA}$0.08 | -0.5689 | 0.4204 | -1.353 | 0.197 |
| $P_{ICA}$0.10 | 1.4109 | 0.4204 | 3.356 | 0.005 |

**Table 18. Analysis of variance for mean solutions.**

| Source | DF | Seq SS | Adj SS | Adj MS | F | P |
|---|---|---|---|---|---|---|
| $Pop_{ICA}$ | 2 | 20.817 | 20.817 | 10.408 | 4.36 | 0.034 |
| decade | 2 | 57.503 | 57.503 | 28.751 | 12.05 | 0.001 |
| $P_{ICA}$ | 2 | 53.902 | 53.902 | 26.951 | 11.30 | 0.001 |
| Residual Error | 14 | 33.400 | 33.400 | 2.386 | | |
| Total | 20 | 165.622 | | | | |

**Table 19. SN ratio solution.**

| Level | $Pop_{ICA}$ | Decade | $P_{ICA}$ |
|---|---|---|---|
| 1 | 22.79 | 22.20 | 22.07 |
| 2 | 23.17 | 22.75 | 23.17 |
| 3 | 21.77 | 22.78 | 21.77 |
| Delta | 1.40 | 0.59 | 1.15 |
| Rank | 1 | 3 | 2 |

**Table 20. Mean solutions.**

| Level | $Pop_{ICA}$ | Decade | $P_{ICA}$ |
|---|---|---|---|
| 1 | 14.48 | 13.63 | 13.53 |
| 2 | 14.93 | 14.28 | 15.11 |
| 3 | 12.89 | 14.39 | 13.66 |
| Delta | 2.05 | 0.76 | 1.58 |
| Rank | 1 | 3 | 2 |

Solution levels are evaluated according to mean solution indices and SN ratios, and factors are ranked to determine the priority or degree of importance of each factor. The mean solution index for each level of each factor can be seen in the solutions table. The ranking of the factors according to the solution analysis concerning SN coefficients and means can be seen in *Tables 19* and *20*. Accordingly, the $Pop_{ICA}$ factor has the highest rank in both tables, and the $P_{ICA}$ factor has the second rank. The ranking of decade factors is the same for the mean solution indices and SN coefficients. Factor interaction analysis is used to fine-tune the levels of factors. These effects can be seen in the following figures (*Figs. 6* and *7*).

As shown in *Fig. 6*, the mean solution index is maximized by $Pop_{ICA}$factor at level 400, by decade factor at level 200, and by $P_{ICA}$ factor at level 0.1. Examining the levels of the factors in *Fig. 7* shows that the factors maximize the SN index at similar levels.

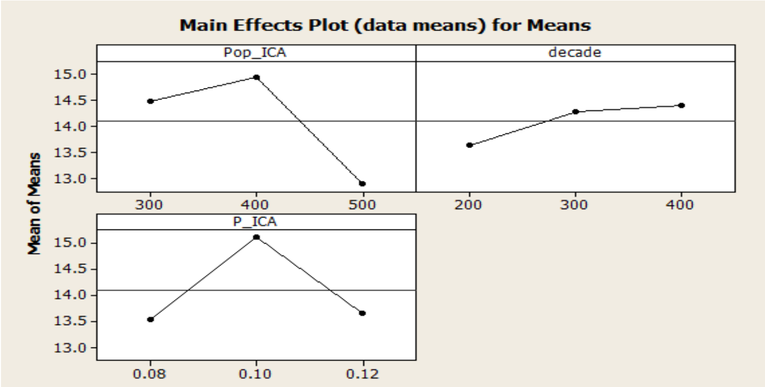


**Fig. 6. Mean solutions.**

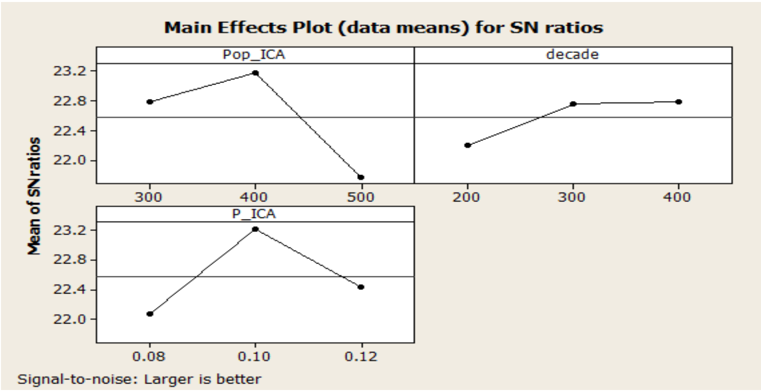


**Fig. 7. Mean SN ratio.**

Thus, the values of the control parameters of the proposed imperialist competitive algorithm are adjusted according to the following table.

**Table 21. Optimal values of control parameters.**

| Factor | Levels |
|---|---|
| $Pop_{ICA}$ | 400 |
| decade | 300 |
| $P_{ICA}$ | 0.1 |

## 4.3 | Evaluation of Algorithms

A Relative Percent Deviation (RPD) is used as a measure for comparing GA and ICA algorithms *Eq. (23)*. Small, medium and large problems are used to measure the performance of these algorithms. The test results, the best solution, the worst solution, the mean solutions, and the mean execution time are presented in *Table 22*. Moreover, *Table 23* shows the RPD values and the mean execution time. The condition for stopping the algorithms is considered to be 100 seconds. Preliminary tests show that these algorithms usually reach the best solution before this time, and the first time they reach the best value of the objective function is recorded.

$$\text{RPD} = \frac{\text{sol}_{\text{avg}} - \text{sol}_{\text{min}}}{\text{sol}_{\text{min}}}. \tag{23}$$

Table 22. Values obtained from different executions for GAMs and both proposed algorithms.

| AP | Runway | GAMS Global Optimal | Time | GA Best | Worst | Mean | Time | ICA Best | Worst | Mean | Time |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 3 | 1 | 0:00:06 | 1 | 1 | 1 | 0:00:16 | 1 | 1 | 1 | 0:00:14 |
| | 5 | 4 | 0:00:09 | 4 | 4 | 4 | 0:00:17 | 4 | 4 | 4 | 0:00:17 |
| | 7 | 9 | 0:00:11 | 9 | 9 | 9 | 0:00:20 | 9 | 9 | 9 | 0:00:19 |
| 6 | 3 | 6 | 0:00:10 | 6 | 6 | 6 | 0:00:30 | 6 | 6 | 6 | 0:00:30 |
| | 5 | 12 | 0:05:42 | 12 | 12 | 12 | 0:00:37 | 11 | 12 | 11.33 | 0:00:33 |
| | 7 | 11 | 0:19:11 | 11 | 11 | 11 | 0:00:43 | 11 | 11 | 11 | 0:00:43 |
| 10 | 3 | 15 | 0:56:01 | 15 | 15 | 15 | 0:01:21 | 15 | 15 | 15 | 0:01:47 |
| | 5 | - | - | 20 | 26 | 21.2 | 0:02:33 | 21 | 26 | 22.2 | 0:02:29 |
| | 7 | - | - | 18 | 22 | 19.4 | 0:03:00 | 14 | 17 | 15.6 | 0:03:21 |
| 20 | 3 | - | - | 47 | 51 | 47.66 | 0:21:36 | 48 | 51 | 49.8 | 0:23:04 |
| | 5 | - | - | 46 | 48 | 46.2 | 0:29:58 | 49 | 50 | 49.5 | 0:27:53 |
| | 7 | - | - | 19 | 25 | 22 | 0:28:46 | 19 | 24 | 23.33 | 0:28:49 |
| 40 | 3 | - | - | 35 | 40 | 36.2 | 0:32:16 | 35 | 39 | 37.8 | 0:30:10 |
| | 5 | - | - | 34 | 37 | 35.6 | 0:38:36 | 36 | 40 | 39.6 | 0:39:23 |
| | 7 | - | - | 16 | 18 | 17.2 | 0:36:34 | 15 | 17 | 16.8 | 0:37:12 |
| 60 | 3 | - | - | 70 | 86 | 72.2 | 0:37:45 | 69 | 73 | 71.2 | 0:36:19 |
| | 5 | - | - | 55 | 61 | 56.6 | 0:38:44 | 58 | 64 | 63.6 | 0:40:55 |
| | 7 | - | - | 68 | 73 | 70 | 0:40:08 | 68 | 74 | 70.2 | 0:41:17 |

Table 23. RPD values and average execution times calculated.

| AP | Runway | GA RPD | Average Computation Time (Sec) | ICA RPD | Average Computation Time (Sec) |
|---|---|---|---|---|---|
| 4 | 3 | 0.00 | 0:00:16 | 0.00 | 0:00:14 |
| | 5 | 0:00 | 0:00:17 | 0:00 | 0:00:17 |
| | 7 | 0:00 | 0:00:20 | 0:00 | 0:00:19 |
| 6 | 3 | 0:00 | 0:00:30 | 0:00 | 0:00:30 |
| | 5 | 0:00 | 0:00:37 | 0:00 | 0:00:33 |
| | 7 | 0:00 | 0:00:43 | 0:00 | 0:00:43 |
| 10 | 3 | 0:00 | 0:01:21 | 0:00 | 0:01:47 |
| | 5 | 0:06 | 0:02:33 | 0:06 | 0:02:29 |
| | 7 | 0:08 | 0:03:00 | 0:11 | 0:03:21 |
| 20 | 3 | 0:01 | 0:21:36 | 0:04 | 0:23:04 |
| | 5 | 0:004 | 0:29:58 | 0:01 | 0:27:53 |
| | 7 | 0:16 | 0:28:46 | 0:23 | 0:28:49 |
| 40 | 3 | 0:03 | 0:32:16 | 0:03 | 0:30:10 |
| | 5 | 0:05 | 0:38:36 | 0:10 | 0:39:23 |
| | 7 | 0:08 | 0:36:34 | 0:12 | 0:37:12 |
| 60 | 3 | 0:03 | 0:37:45 | 0:03 | 0:36:19 |
| | 5 | 0:07 | 0:38:44 | 0:10 | 0:40:55 |
| | 7 | 0:03 | 0:40:08 | 0:03 | 0:41:17 |

Statistical results indicate that GA performs better than the ICA algorithm. The mean plot with LSD intervals for the two algorithms is shown in *Fig. 8* for further analysis of the results. According to the tables above and the figure below, the values of the objective function and the execution time in both GA and ICA algorithms are close to each other. The GA algorithm performs better than the ICA algorithm in terms of both the value of the objective function and the execution time.

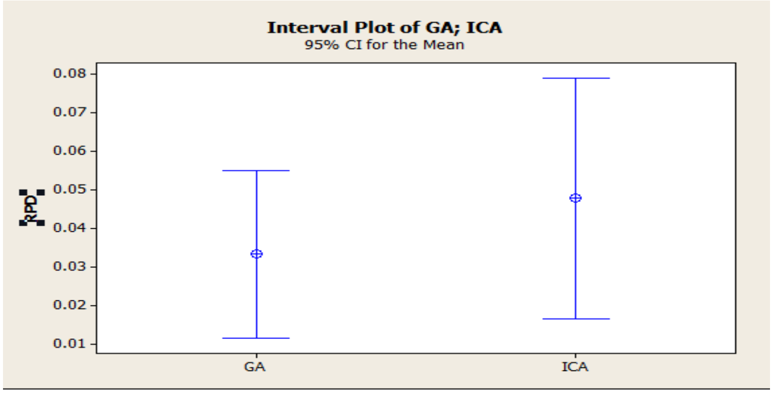


**Fig. 8. Mean plot and LSD intervals (95% confidence level) for GA and ICA algorithms.**

RPD values for different numbers of aircraft and runways are shown in *Figs. 9* and *10*.

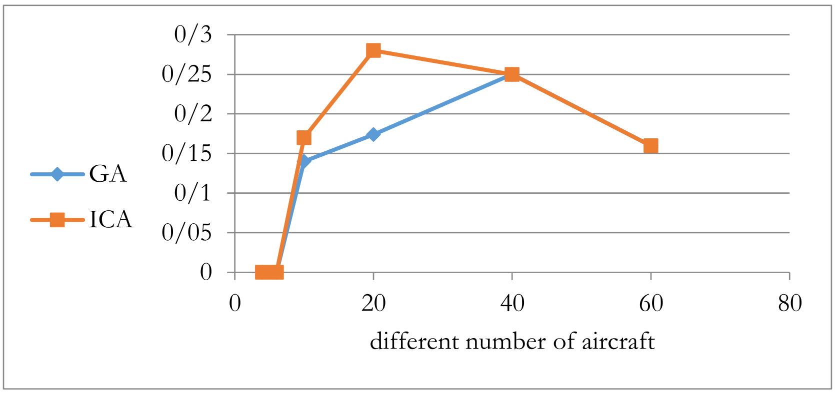


**Fig. 9. RPD values for different number of aircraft.**

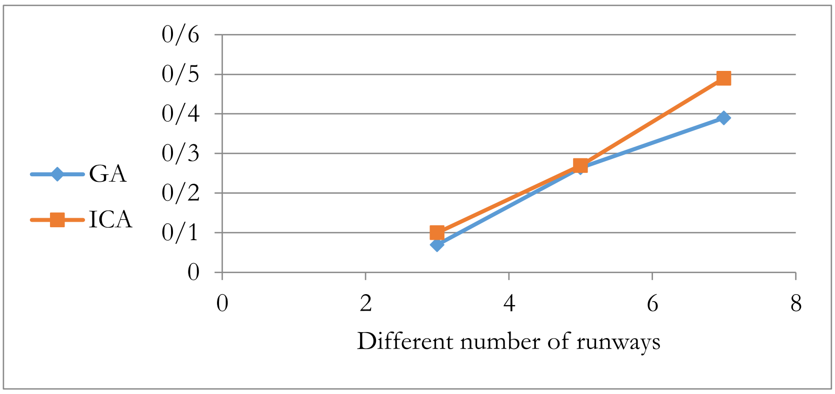


**Fig. 10. RPD values for different number of runways.**

As shown in *Figs. 9* and *10*, as the number of aircraft and runways increases, the difference between the performances of the two proposed algorithms is greatly reduced.

## 5 | Conclusion

This is conducted to solve the aircraft take-off and landing problem in situations where take-off and landing times are uncertain and aircraft also have access restrictions. It also considers the possibility of runway disturbances and the time required to repair the runway. None of the previous studies have examined the assumption of the possibility of runway disturbances, the time required to repair the runway, the lack of access to aircraft at certain times, and the uncertainty of take-off and landing times at the same time. On the other hand, finding the sequence of landing and take-off on runways to minimize the total delay and

haste in take-off and landing of aircraft is one of the most difficult problems of combined optimization even on a medium scale. In this study, a new integer scheduling model for the flexible airline scheduling problem is provided to minimize the total weight of aircraft delays and haste considering constraints such as aircraft's ready time, runway disruptions, limited aircraft access, and runway access time. The computational difficulties of this problem have made it impossible to solve it accurately on a large scale. According to studies, this is an NP-hard problem even for airport scheduling mode, which becomes almost impossible to solve through precise methods and optimization software as the number of aircraft increases. So, the use of heuristic and meta-heuristic algorithms can be helpful. GA and ICA algorithms are used to solve the problem.

We first designed the corresponding mathematical programming model to solve the problem studied in this research work. Then, we presented the robust counterpart of the problem model using a robust planning approach. We solved the problem with certain and uncertain conditions and discussed several scenarios for parameters involved in the solution. Finally, we solved the problem using genetic and imperialist competitive algorithms concerning its complicated structure. For this purpose, we proposed the GA and imperialist competitive algorithm to solve this problem and employed different parameters for them.

Based on obtained results, the mathematical programming model can be solved in a shorter time and with sufficient accuracy. It is because that the data from the studied sample is such that we are not dealing with a large-scale problem at first, and metaheuristic algorithms cannot compete with the exact methods such as the branch and bound algorithm in terms of execution time and solution quality. Therefore, it is observed that the exact method solution is more accurate than that of the genetic and imperialist competitive algorithm employed in this study. But the results show the ability of algorithms which are applied to solve this model. The presented algorithm can provide acceptable solutions for problems, which cannot be solved by exact methods and different solvers such as CPLEX in a reasonable time.

In this study, the problem is investigated in terms of the number of aircraft and runways to evaluate the algorithms used. The results confirm the correct operation of the algorithms. According to the results, further studies are recommended to use accurate problem-solving methods such as the Benders decomposition algorithm or variable neighborhood descent meta-heuristic algorithm. It is also recommended that fuzzy theory and logic of gray numbers be used in the mathematical model and that the results be compared with this study.

## Reference

[1] Zeng, Y., Che, A., & Wu, X. (2018). Bi-objective scheduling on uniform parallel machines considering electricity cost. *Engineering optimization*, *50*(1), 19-36.

[2] Ng, K. K. H., Lee, C. K., Chan, F. T., Chen, C. H., & Qin, Y. (2020). A two-stage robust optimisation for terminal traffic flow problem. *Applied soft computing*, *89*, 106048. https://doi.org/10.1016/j.asoc.2019.106048

[3] Lambelho, M., Mitici, M., Pickup, S., & Marsden, A. (2020). Assessing strategic flight schedules at an airport using machine learning-based flight delay and cancellation predictions. *Journal of air transport management*, *82*, 101737. https://doi.org/10.1016/j.jairtraman.2019.101737

[4] Zhang, J., Zhao, P., Zhang, Y., Dai, X., & Sui, D. (2020). Criteria selection and multi-objective optimization of aircraft landing problem. *Journal of air transport management*, *82*, 101734. https://doi.org/10.1016/j.jairtraman.2019.101734

[5] Yang, S., Yan, Y., & Chen, P. (2021). Robust optimization models for flight rerouting. *International journal of computational methods*, *18*(05), 2040001. https://doi.org/10.1142/S0219876220400010

[6] Shakibayifar, M., Sheikholeslami, A., Corman, F., & Hassannayebi, E. (2020). An integrated rescheduling model for minimizing train delays in the case of line blockage. *Operational research*, *20*, 59-87.

[7] Çiftçi, M. E., & Özkır, V. (2020). Optimising flight connection times in airline bank structure through Simulated Annealing and Tabu Search algorithms. *Journal of air transport management*, *87*, 101858. https://doi.org/10.1016/j.jairtraman.2020.101858

[8] Sama, M., D'Ariano, A., Palagachev, K., & Gerdts, M. (2019). Integration methods for aircraft scheduling and trajectory optimization at a busy terminal manoeuvring area. *Or spectrum*, *41*, 641-681.

[9] Esmaeilidouki, A., Mahzouni-Sani, M., Nikhalat Jahromi, A., & Jolai, F. (2021). A novel fuzzy bi-objective vehicle routing and scheduling problem with time window constraint for a distribution system: a case study. *Scientia Iranica*, *28*(5), 2868-2889.

[10] Salehipour, A., Modarres, M., & Naeni, L. M. (2013). An efficient hybrid meta-heuristic for aircraft landing problem. *Computers & operations research*, *40*(1), 207-213.

[11] Zhou, Q., Zhang, Y., Li, Z., Li, J., Xu, H., & Olatunbosun, O. (2017). Cyber-physical energy-saving control for hybrid aircraft-towing tractor based on online swarm intelligent programming. *IEEE transactions on industrial informatics*, *14*(9), 4149-4158.

[12] Arkind, K. (2004). Requirements for a novel terminal area capacity enhancement concept in 2022. *AIAA guidance, navigation, and control conference and exhibit* (p. 5411), Providence, Rhode Island. https://doi.org/10.2514/6.2004-5411

[13] Idris, H., Delcaire, B., Anagnostakis, I., Hall, W., Pujet, N., Feron, E., Hansman R., Clarke J. P., & Odoni, A. (1998). Identification of flow constraint and control points in departure operations at airport systems. *Guidance, navigation, and control conference and exhibit* (p. 4291), Boston, MA, U.S.A. https://doi.org/10.2514/6.1998-4291

[14] Sinha, D. (2019). *Deregulation and liberalisation of the airline industry: Asia, Europe, North America and Oceania*. Routledge.

[15] Sama, M., D'Ariano, A., Corman, F., & Pacciarelli, D. (2017). Metaheuristics for efficient aircraft scheduling and re-routing at busy terminal control areas. *Transportation research part C: emerging technologies*, *80*, 485-511.

[16] Fernandes, H. F., & Müller, C. (2019). Optimization of the waiting time and makespan in aircraft departures: A real time non-iterative sequencing model. *Journal of air transport management*, *79*, 101686. https://doi.org/10.1016/j.jairtraman.2019.101686

[17] Lieder, A., & Stolletz, R. (2016). Scheduling aircraft take-offs and landings on interdependent and heterogeneous runways. *Transportation research part E: logistics and transportation review*, *88*, 167-188.

[18] Lee, S., Hong, Y., & Kim, Y. (2020). Optimal scheduling algorithm in point merge system including holding pattern based on mixed-integer linear programming. *Proceedings of the institution of mechanical engineers, part G: journal of aerospace engineering*, *234*(10), 1638-1647.

[19] Allahverdi, A., Ng, C. T., Cheng, T. E., & Kovalyov, M. Y. (2008). A survey of scheduling problems with setup times or costs. *European journal of operational research*, *187*(3), 985-1032.

[20] Ball, M., Barnhart, C., Nemhauser, G., & Odoni, A. (2007). Air transportation: irregular operations and control. *Handbooks in operations research and management science*, *14*, 1-67.

[21] Zhan, Z. H., Zhang, J., Li, Y., Liu, O., Kwok, S. K., Ip, W. H., & Kaynak, O. (2010). An efficient ant colony system based on receding horizon control for the aircraft arrival sequencing and scheduling problem. *IEEE transactions on intelligent transportation systems*, *11*(2), 399-412.

[22] Khaksar, H., & Sheikholeslami, A. (2019). Airline delay prediction by machine learning algorithms. *Scientia Iranica*, *26*(5), 2689-2702.

[23] Beasley, J. E., Krishnamoorthy, M., Sharaiha, Y. M., & Abramson, D. (2004). Displacement problem and dynamically scheduling aircraft landings. *Journal of the operational research society*, *55*(1), 54-64.

[24] Bennell, J. A., Mesgarpour, M., & Potts, C. N. (2013). Airport runway scheduling. *Annals of operations research*, *204*, 249-270.

[25] Hu, XB., Di Paolo, E. (2009). An efficient genetic algorithm with uniform crossover for the multi-objective airport gate assignment problem. In *multi-objective memetic algorithms* (pp. 71-89). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-88051-6_4

[26] Bennell, J. A., Mesgarpour, M., & Potts, C. N. (2017). Dynamic scheduling of aircraft landings. *European journal of operational research*, *258*(1), 315-327.

[27] Kenan, N., Jebali, A., & Diabat, A. (2018). An integrated flight scheduling and fleet assignment problem under uncertainty. *Computers & operations research*, *100*, 333-342.

[28] Cheng, C. B., Shyur, H. J., & Kuo, Y. S. (2014). Implementation of a flight operations risk assessment system and identification of critical risk factors. *Scientia Iranica*, *21*(6), 2387-2398.

[29] Kim, S., Suh, W., & Kim, J. (2015). Forecasting hourly traffic volume: Incheon international airport access road. *Scientia Iranica*, *22*(4), 1510-1516.

[30] Tavakkoli Moghaddam, R., Yaghoubi-Panah, M., & Radmehr, F. (2012). Scheduling the sequence of aircraft landings for a single runway using a fuzzy programming approach. *Journal of air transport management*, *25*, 15-18.

[31] Rashidi Komijan, A., Tavakkoli-Moghaddam, R., & Dalil, S. A. (2021). A mathematical model for an integrated airline fleet assignment and crew scheduling problem solved by vibration damping optimization. *Scientia Iranica*, *28*(2), 970-984.

[32] Hassanpour, A., Bagherinejad, J., & Bashiri, M. (2019). A robust bi-level programming model for designing a closed-loop supply chain considering government's collection policy. *Scientia Iranica*, *26*(6), 3747-3764.

[33] Ben-Tal, A., & Nemirovski, A. (1999). Robust solutions of uncertain linear programs. *Operations research letters*, *25*(1), 1-13.

Tohidi Nasab et al. | Int. J. Res. Ind. Eng. 12(1) (2023) 21-42